Intergenerational Mobility in Switzerland

A Comparison of Methodological Approaches

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Overview

- Introduction
- Data
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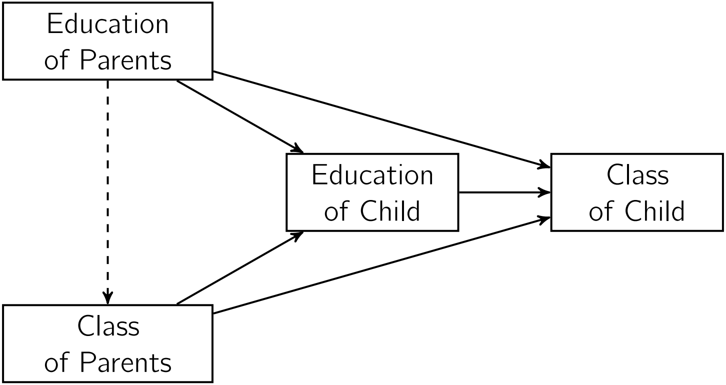
Introduction

- Equal opportunity principle in meritocratic societies
  - The social position an individual can achieve should only depend on own effort/merit, but not on *ascriptive* characteristics such as, e.g., social origin or gender.
- Societies in which equal opportunity is granted are called "open". They are characterized by high *social mobility*.
  - Mobility is usually understood as "equality of opportunity" – the outcomes may be unequal, but everyone, regardless of starting point, can have the same opportunity to get a good result. (Hout 2004: 970)
- To evaluate the openness of a society we can therefore analyze the degree to which the social position of an individual depends on the status of the individual's parents.

Introduction

- International research shows that in most countries sizable effects of social origin do exists and persist over time. This indicates that in these societies the principle of equal opportunity is violated.
- Yet, only little research on the topic exists for Switzerland. In particular, from the existing literature it is unclear whether social mobility increased - as asserted by modernization theories (e.g. Lipset/Bendix 1959, Kerr et al. 1960, Blau/Duncan 1967) - or not.
- We therefore started a project to analyze the changes in social mobility in Switzerland over time.
- In particular, we analyze how *educational attainment* and *social class* of respondents depend on the education and class of their parents.

Introduction



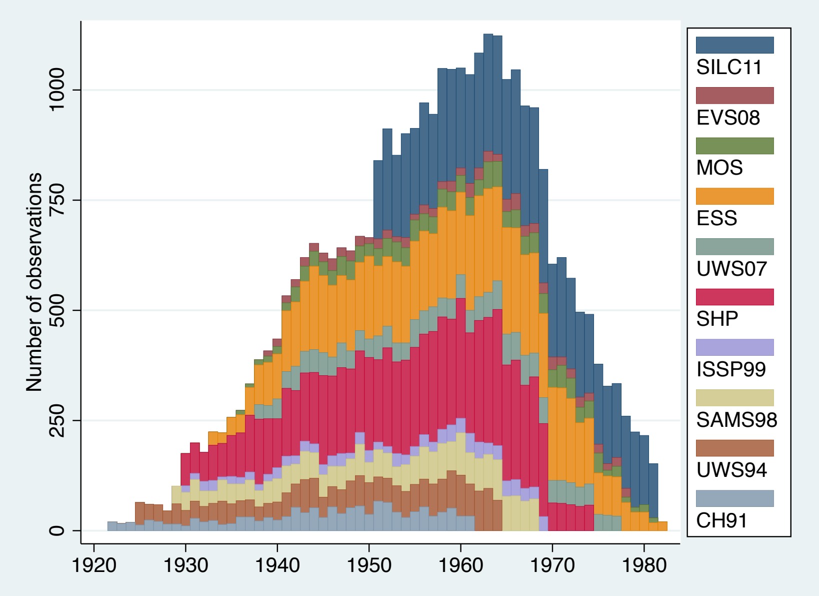
Data

- Required are data that contain the relevant status variables for the respondents as well as information about education and occupation of parents.
- Most large-scale surveys, such as the official surveys by the Federal Statistical Office, do not contain information on parents.
- Nonetheless, we were able to identify a number of surveys that can be used for these types of analyses. The results below are based on a selection of these surveys. More surveys are available (especially some older ones) and will be incorporated in future.
- We harmonized the variables in the different surveys to build a common database that can be analyzed in terms of birth cohorts. The age range of respondents we restricted to 30 through 69.

Data: Surveys

Survey	Year/Wave	*N*	Code
Les Suisses et leur société	1991	1331	CH91
Schweizer Umweltsurvey	1994	2233	UWS94
	2007	1973	UWS07
Swiss Labor Market Survey 1998	1998	2340	SAMS98
ISSP "Social inequality"	1999	972	ISSP99
Swiss Household Panel	1999	5365	SHP99
	2004	2420	SHP04
European Social Survey	2002	1450	ESS02
	2004	1457	ESS04
	2006	1267	ESS06
	2008	1187	ESS08
	2010	985	ESS10
	2012	945	ESS12
MOSAiCH	2005	741	MOS05
	2011	819	MOS11
European Values Study 2008	2008	830	EVS08
Statistics on Income and Living Conditions 2011	2011	6753	SILC11
Total		33068	

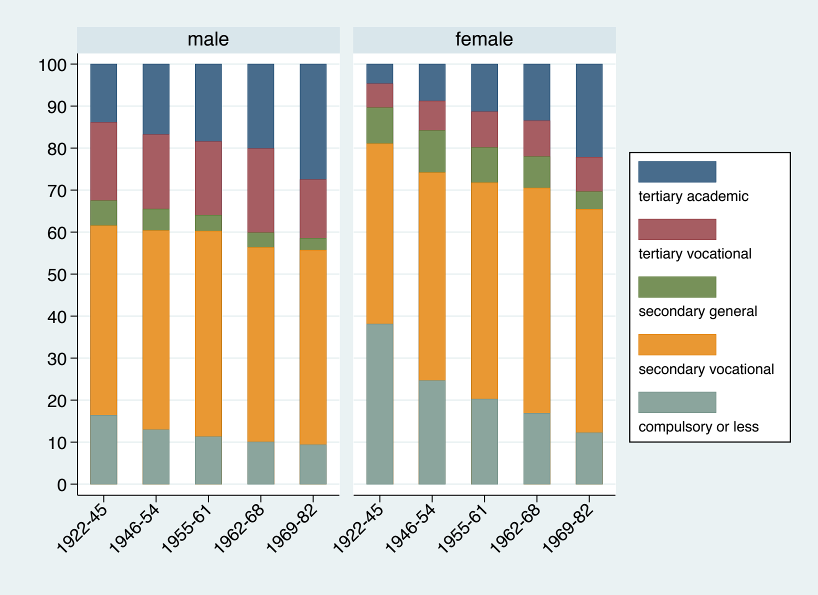
Data: Number of Observations by Birthyear



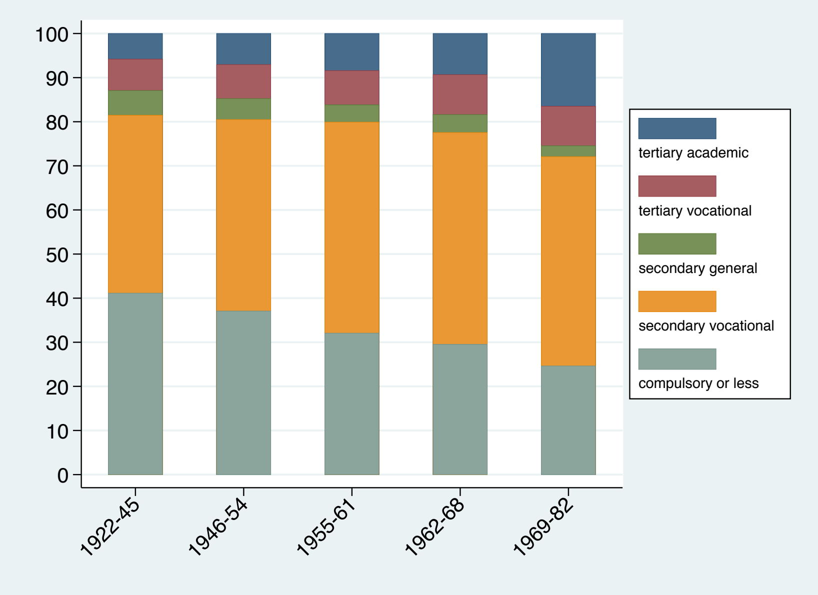
Data: Education

	Education categorie	Included levels of education
1	compulsory or less	No formal education; compulsory education; one year vocational training
2	secondary vocational	Vocational training and education; general education without baccalaureate
3	secondary general	General education with baccalaureate; vocational baccalaureate; college of education (without university of education)
4	tertiary vocational	Professional education and training; advanced federal professional and training diploma; professional education college; university of applied sciences; university of education
5	tertiary academic	University; federal institute of technology

Data: Education by birth cohorts



Data: Parent's education by respondents birth cohort

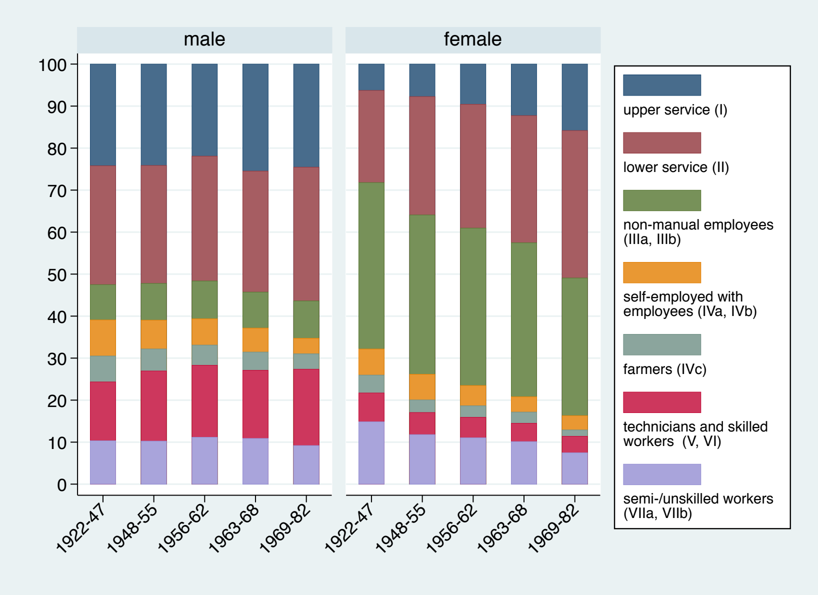


Data: Class (EGP)

EGP Class		Description
I	Upper service	Higher-grade professionals, administrators and officials; managers in large industrial establishments; large proprietors
II	Lower service	Lower-grade professionals, administrators and officials; higher-grade technicians; managers in small business and industrial establishments; supervisors of nonmanual employees
III	Non-manual employee	Routine non-manual employees in administration and commerce; sales personnel; other rank-and-file service workers
IVa,b	Self-employed	Small proprietors, artisans, etc., with employees (IVa); without employees (IVb)
IVc, VIIb	Farmers	Farmers and smallholders, self-employed fishermen (IVc); Agricultural workers (VIIb)
V, VI	Technicians and skilled workers	Lower-grade technicians; supervisors of manual workers; skilled manual workers
VIIa,b	Semi-/unskilled workers	Semi- and unskilled manual workers

EGP classification following Erikson, Goldthorpe and Portocarero (1983: 307)

Data: Class by birth cohorts



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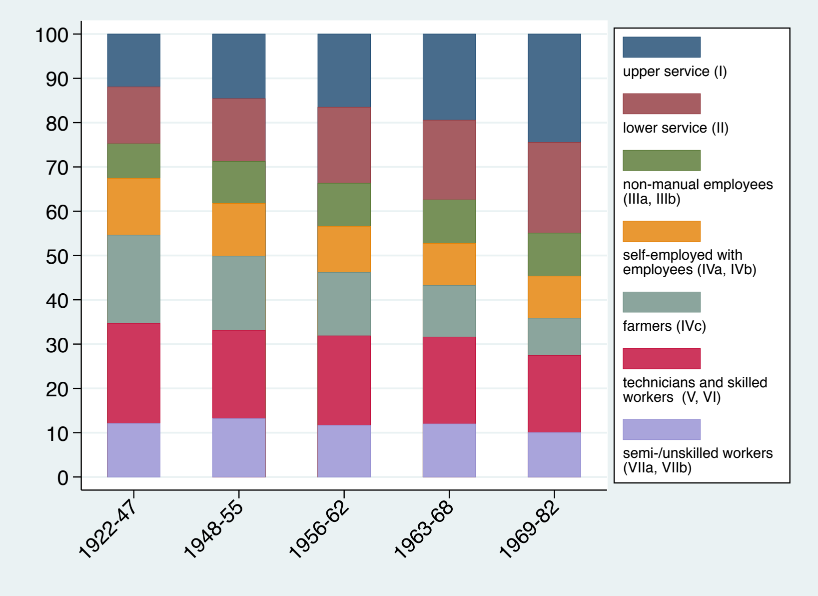

Mobility tables

- To study the relation between parent's characteristics and child's achievements, so called mobility tables can be used.
- A mobility table is a two-way table of, for example, parent's education against child's education. The pattern of cell counts in such a table provides evidence about the degree to which child's education depends on parent's education.

Mobility tables: Example

- Relation between respondent's education and parent's education (males, birth cohorts 1969-82, N = 2485, column percent)

	Respondent's education			
Parent's education	compulsory	secondary	tertiary	Total
compulsory	73.1	25.5	11.7	24.2
secondary	18.1	62.0	41.7	49.5
tertiary	8.8	12.6	46.6	26.3
Total	100.0	100.0	100.0	100.0
Row percent	9.3	49.2	41.5	100.0

Mobility tables: How much mobility is in this table?

- Total mobility
  - Percentage of respondents whose educational achievement is unequal the education of their parents
  - (N – Sum of diagonal) / N
  - Could also be divided into upward mobility and downward mobility
- Chance mobility
  - Expected amount of mobility if respondents' education is independent from parents' education
- Structural mobility
  - Minimum amount of mobility required to move from parents' educational distribution to respondents' educational distribution
  - (Absolute deviations between marginal distributions) / 2N
- Circular mobility: Total mobility – structural mobility
- Relative mobility
  - Circular mobility / (Chance mobility – Structural mobility)

Mobility tables: How much mobility is in this table?

- Total mobility T

$$T = \frac{2485 - (170 + 757 + 480)}{2485} = 43.4\%$$

- Chance mobility I

$$I = \frac{2485 - \left(\frac{232*602}{2485} + \frac{1222*1229}{2485} + \frac{1031*654}{2485}\right)}{2485} = 62.5\%$$

	Respondent's education			
Parent's education	compulsory	secondary	tertiary	Total
compulsory	170	311	121	602
secondary	42	757	430	1229
tertiary	20	154	480	654
Total	232	1222	1031	2485

Mobility tables: How much mobility is in this table?

- Structural mobility S

$$S = \frac{|232 - 602| + |1222 - 1229| + |1031 - 654|}{2 * 2485} = 15.2\%$$

- Circular mobility C

$$C = T - S = 43.4\% - 15.2\% = 28.2\%$$

- Relative mobility R

$$R = C/(I - S) = 28.2/(62.5 - 15.2) = 59.6\%$$

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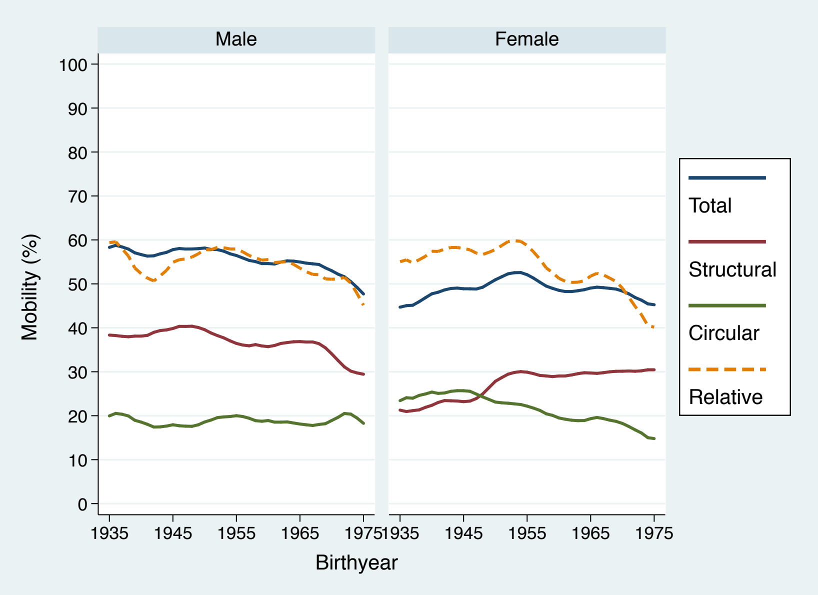
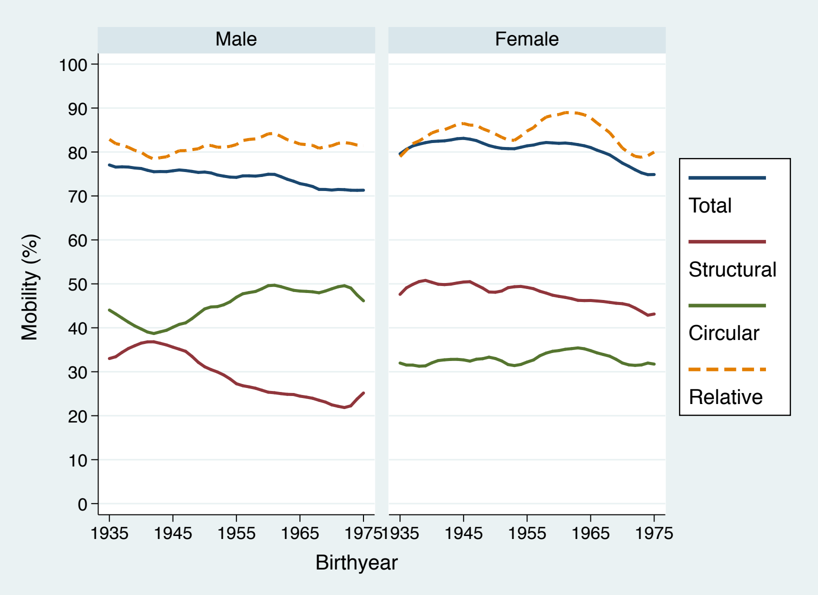
Mobility tables

- The above statistics can be computed based on mobility tables for different birth cohorts to observe how social mobility changes over time.
- In the following this is done for education and class, separately for males and females.
- To obtain a smooth curve over birth cohorts we compute the mobility tables for specific birth years including surrounding years by means of kernel weights (bandwidth 5 years).

Social mobility over time: Education



Social mobility over time: Class



Log-linear Models

- Such simple mobility table analyses can provide some first insights. However, a more sophisticated approach to measure the degree of dependence in a mobility table net of structural change are so called log-linear models.
- Given is a two-way frequency table (e.g. respondent's educational achievement by education of parents):

R \ C	$F_{.,1}$	$F_{.,2}$	$F_{.,3}$	$F_{.,+}$
$F_{1,.}$	$F_{1,1}$	$F_{1,2}$	$F_{1,3}$	$F_{1,+}$
$F_{2,.}$	$F_{2,1}$	$F_{2,2}$	$F_{2,3}$	$F_{2,+}$
$F_{3,.}$	$F_{3,1}$	$F_{3,2}$	$F_{3,3}$	$F_{3,+}$
$F_{+,.}$	$F_{+,1}$	$F_{+,2}$	$F_{+,3}$	$F_{+,+}$

Log-linear Models

- The observed cell frequencies in such a table can been expressed as:

$$F_{ij} = \underbrace{\tau \;\cdot\; \tau_i \;\cdot\; \tau_j}_{\text{Marginal dist.}} \cdot \tau_{ij}$$

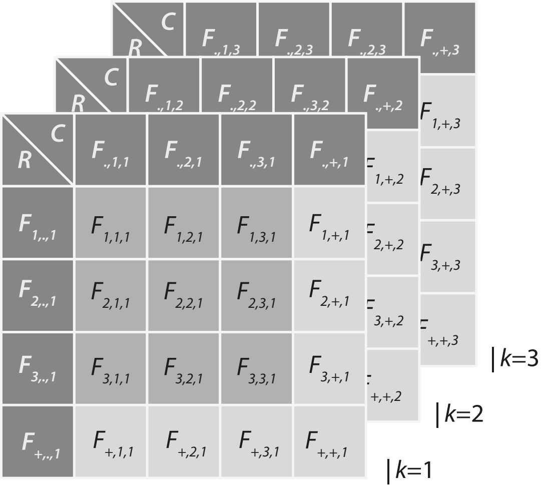
  where i stands for the row and j for the column.

- This is called a "log-linear model" because taking the logarithm leads to a linear expression:

$$\begin{aligned}\log(F_{ij}) &= \log(\tau) + \log(\tau_i) + \log(\tau_j) + \log(\tau_{ij}) \\ &= \mu + \mu_i + \mu_j + \mu_{ij}\end{aligned}$$

Log-Linear Models

- Now think of a table with an additional dimension (e.g. birth cohorts):



Log-Linear Models

- Such a three-dimensional table can be expressed as follows (saturated model):

$$F_{ijk} = \underbrace{\tau \cdot \tau_k \cdot \tau_i \cdot \tau_j}_{\text{Unconditional margins}} \cdot \underbrace{\tau_{ik} \cdot \tau_{jk} \cdot \tau_{ij}}_{\text{Conditional margins}} \cdot \tau_{ijk}$$

  where k stands for the additional dimension.
- Goal: Find a more parsimonious model to describe the variation in the association between rows and columns over k.

Log-Linear Models

- Log-Multiplicative Layer Effect Model (LMLEM) (Xie 1992): Restrict the saturated model

$$F_{ijk} = \tau \cdot \tau_k \cdot \tau_i \cdot \tau_j \cdot \tau_{ik} \cdot \tau_{jk} \cdot \underbrace{\tau_{ij} \cdot \tau_{ijk}}$$

  to

$$F_{ijk} = \tau \cdot \tau_k \cdot \tau_i \cdot \tau_j \cdot \tau_{ik} \cdot \tau_{jk} \cdot \overbrace{\exp(\psi_{ij} \cdot \phi_k)}$$

- Parameter ψ_{ij} describes the baseline pattern of deviations from independence given the marginal distributions (common pattern over all k).
- Parameter ϕ_k is a scaling factor specific to subtable k. It indicates how pronounced the deviations pattern is in subtable k.
- That is, ϕ_k indicates how strong the association between rows (parents' education) and columns (respondents's education) is in subtable (birthcohort) k.

LMLEM Results: Education

LMLEM Results: Class (EGP)

PRE Approach

- The Log-Multiplicative Layer Effect Model has often been used to analyze changes in intergenerational mobility over birth cohorts. The model, however, has some disadvantages.
  - First, it assumes a common baseline pattern of associations that remains constant over time. This assumption may be violated so that results are biased.
  - Second, it is difficult to extend the model to include control variables.
  - Third, there is no clear interpretation of the absolute values of ϕ_k. In fact, the overall level of the ϕ_k parameters is meaningless, because the sum over ϕ_k^2 is restricted to 1. This implies that ϕ_k cannot be compared across models.
- We therefore propose an alternative approach that is based on (categorical) regression models and the PRE principle (see Jann and Combet 2012)

PRE Approach

- General ideas
  - The stronger the effect of the status of the parents on the status of their children, the lower is intergenrational mobility.
  - The „strength“ of an effect is easy to conceptualize for single regression coefficients. Things get more complicated, however, if we have to determine the strength of an effect that comprises multiple parameters.
  - Instead of thinking in terms of model parameters, however, we can ask how "useful" the information on parents is to predict the status of their children.
  - The better the position of children can be predicted based on parents characteristics, the stronger is the influence of social origin and the lower is social mobility.
  - To quantify the predictive power of parents' characteristics we can resort to the statistical concept of the Proportional Reduction of Error (PRE).

PRE Approach

- Formally:

$$PRE = \frac{E_0 - E_1}{E_0} = 1 - \frac{E_1}{E_0}$$

  where E_0 is the sum of prediction errors under limited information and E_1 is the sum of prediction errors under full information.

- Different error rules can be applied, yielding different PRE measures. Because our dependent variables are categorical, a sensible error rule – based on information theory (see Theil 1970) – is

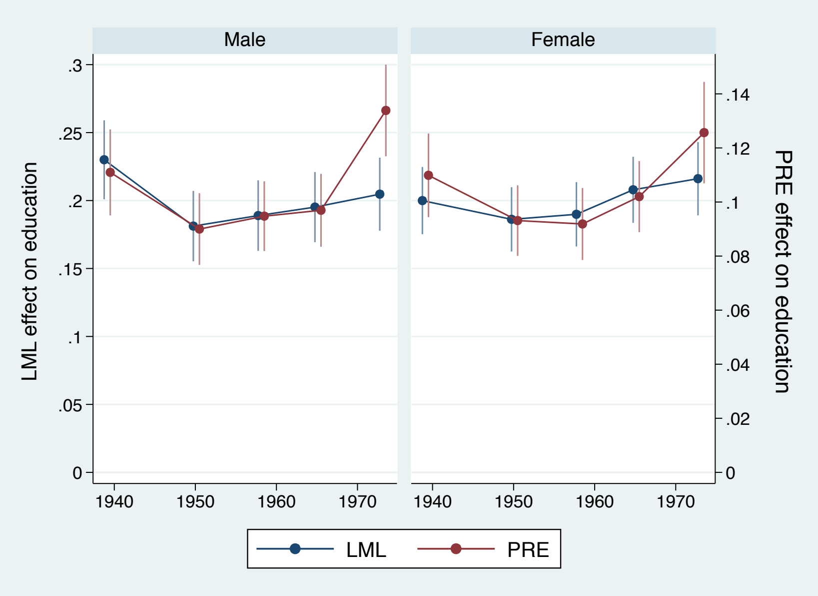
$$E_j = -\sum_{i=1}^{N} w_i \ln\left(\widehat{P}_j(Y = y_i)\right), \quad j = 0, 1$$

  where w_i is the respondent's survey weight.

PRE Approach

- $\widehat{P}_j(Y = y_i)$ is the predicted probability of the dependent variable taking on value y_i, where y_i is the observed value for respondent i.
- In our context, we use multinomial logistic regression to estimate there probabilities.
  - Restricted model ($j = 0$): Model without parents' variables as predictors
  - Full model ($j = 1$): Model including parents' variables as predictors
- For each birth cohort, we fit separate models. That is, the approach is fully flexible across cohorts and does not assume some sort of stable association pattern.
- The resulting PRE values then indicate how social mobility changed across cohorts.

PRE Results (compared to LMLEM): Education

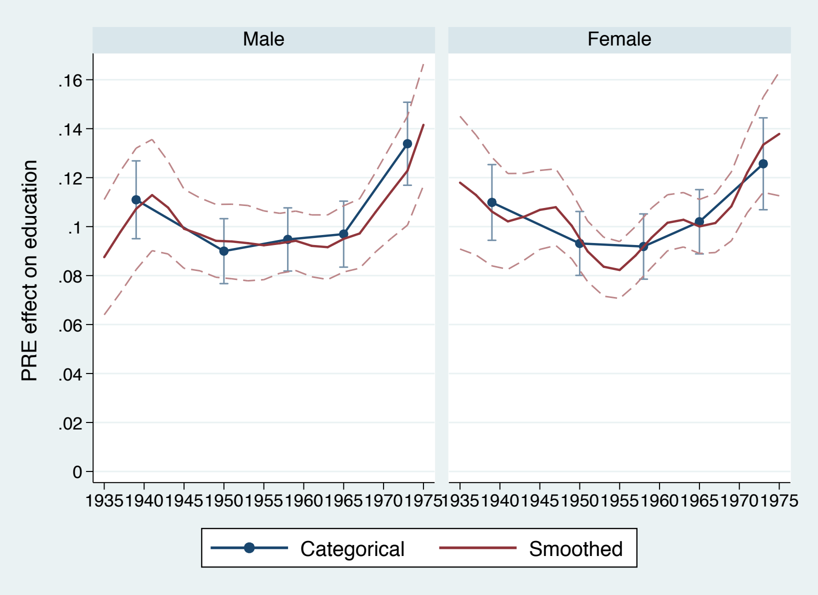


PRE Results (compared to LMLEM): Class

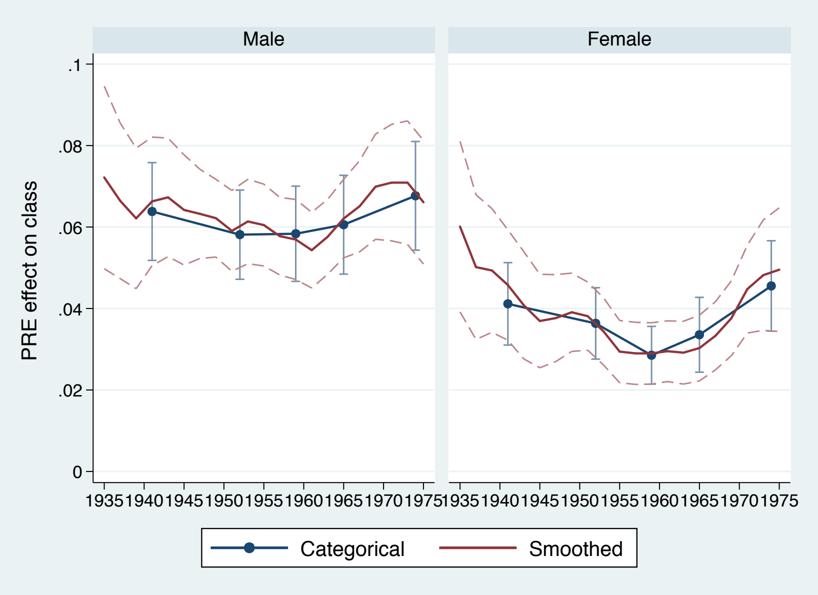
PRE Approach: Smoothing

- To obtain a more detailed picture, PRE can also be computed for single birth years. However, data limitations would lead to a wiggly curve with wide confidence intervals.
- To stabilize model estimates and smooth the curve we again use kernel weights (bandwidth 5 years) to select observations to be included in a model for a specific time point.
- Observations of the target birth year receive the largest weights, observations of surrounding birth years receive weights that decrease the larger the difference to the target birth year. Weights are zero if the difference is 5 or more years.

Smoothed PRE: Results for Education



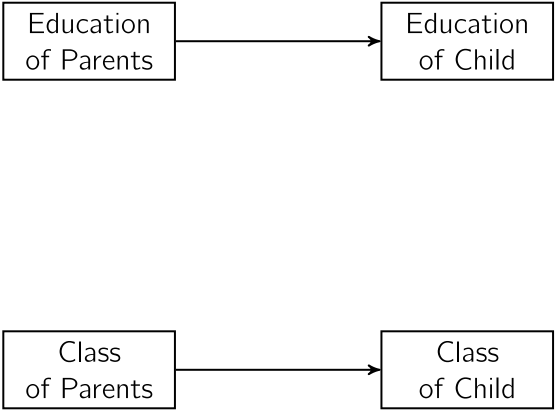
Smoothed PRE: Results for Class



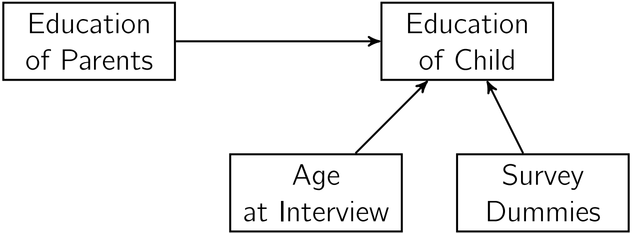
PRE: Extensions

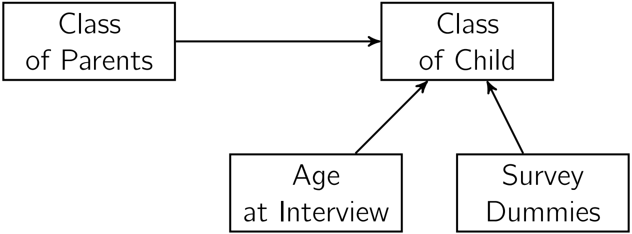
- PRE has several advantages
  - It is easy to incorporate control variables (e.g. age, survey dummies, etc.)
  - Several origin variables can be used in the same model (education, class, father, mother)
  - Effects can be decomposed into direct and indirect effects.

PRE: Control Variables

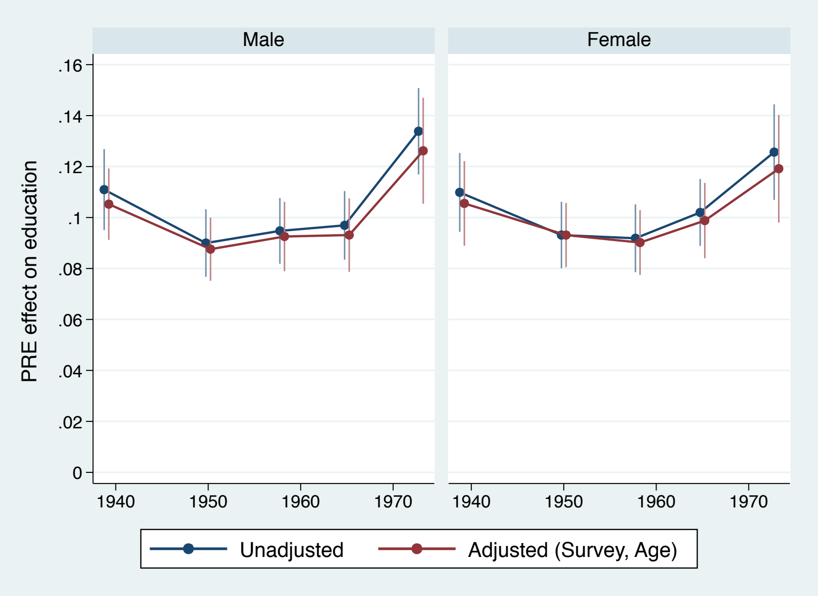


PRE: Control Variables

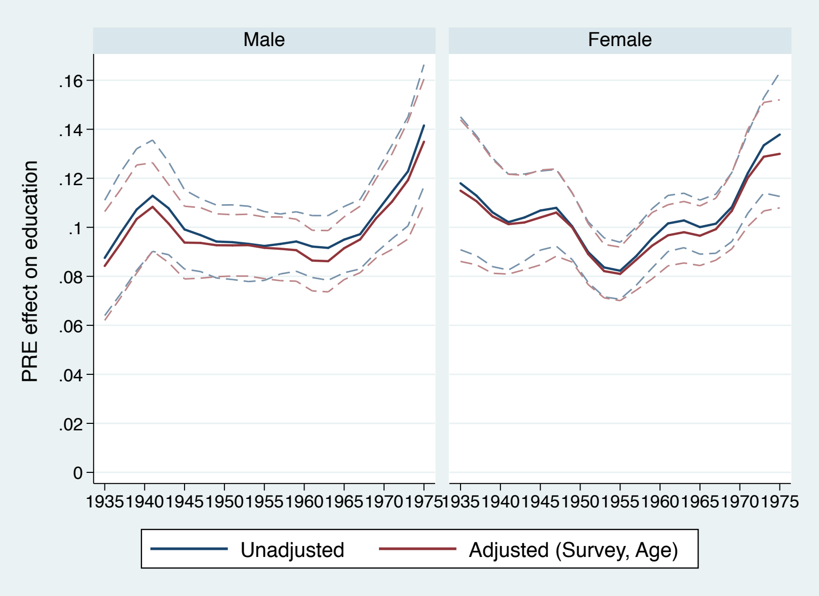




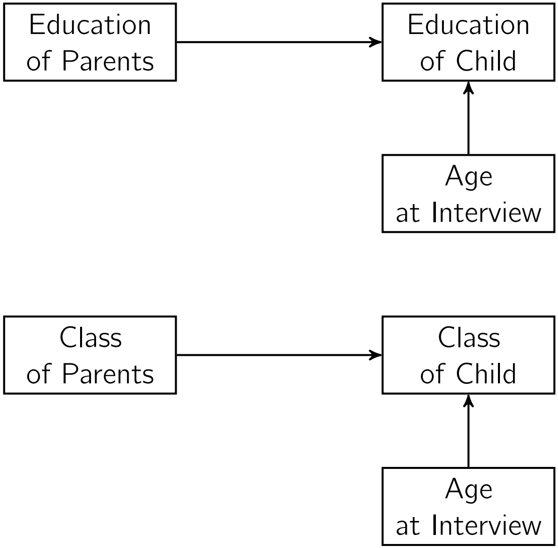
PRE: Control Variables



PRE: Control Variables



PRE: Multiple Origin Variables



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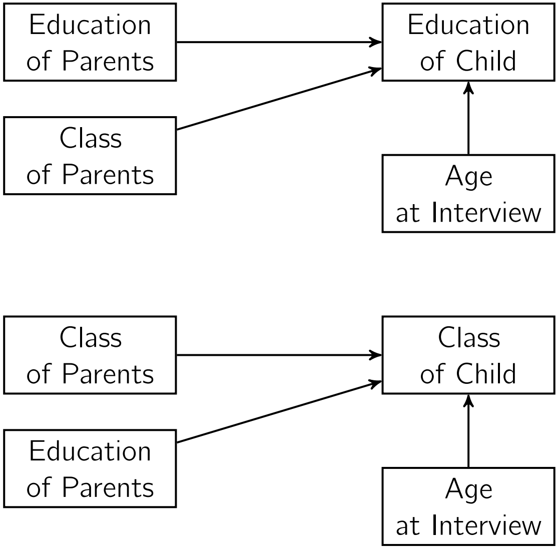
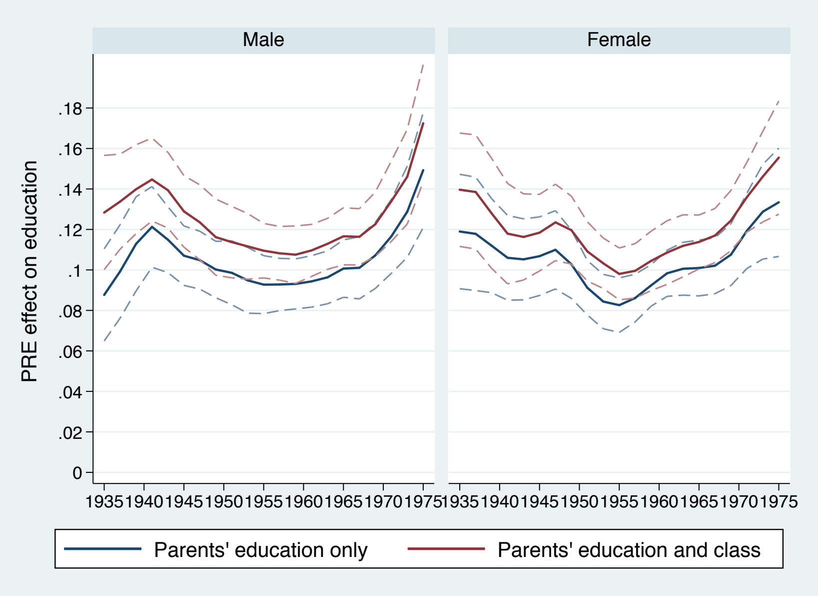
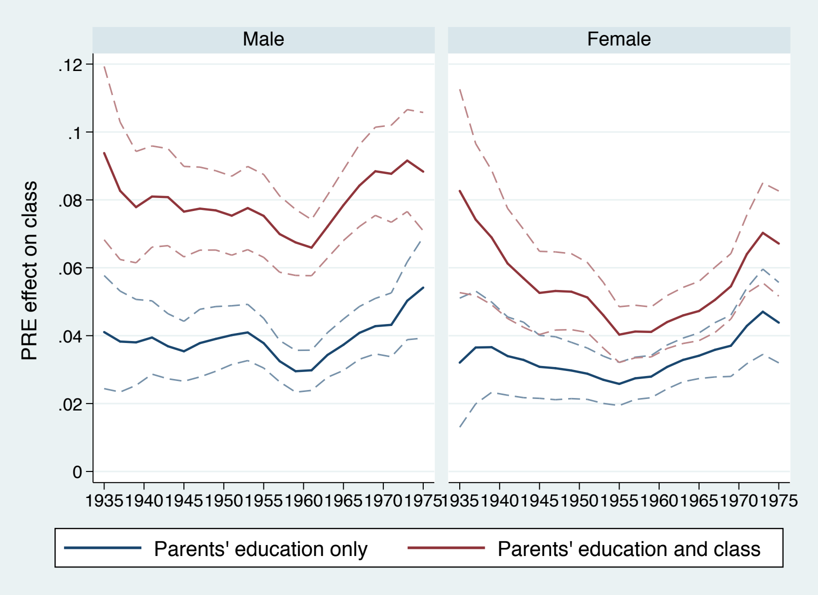


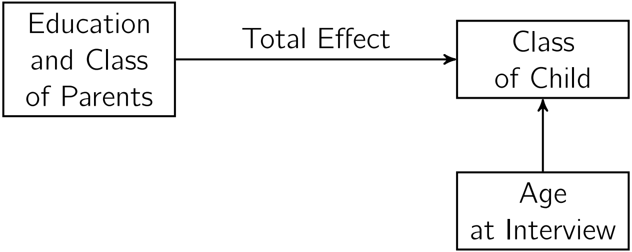
PRE: Multiple Origin Variables



PRE: Multiple Origin Variables



PRE: Decomposition (direct and indirect effetcs)



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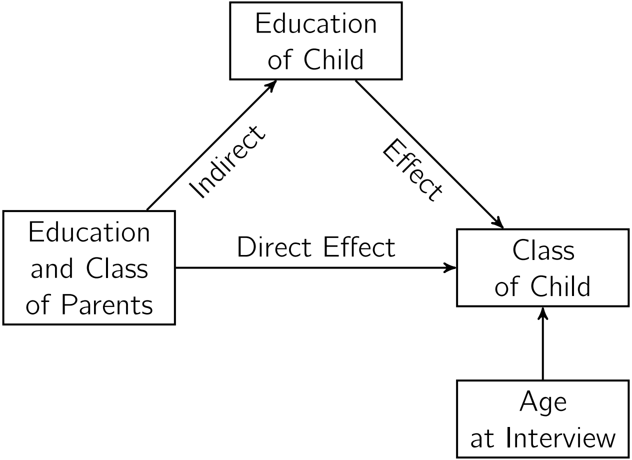

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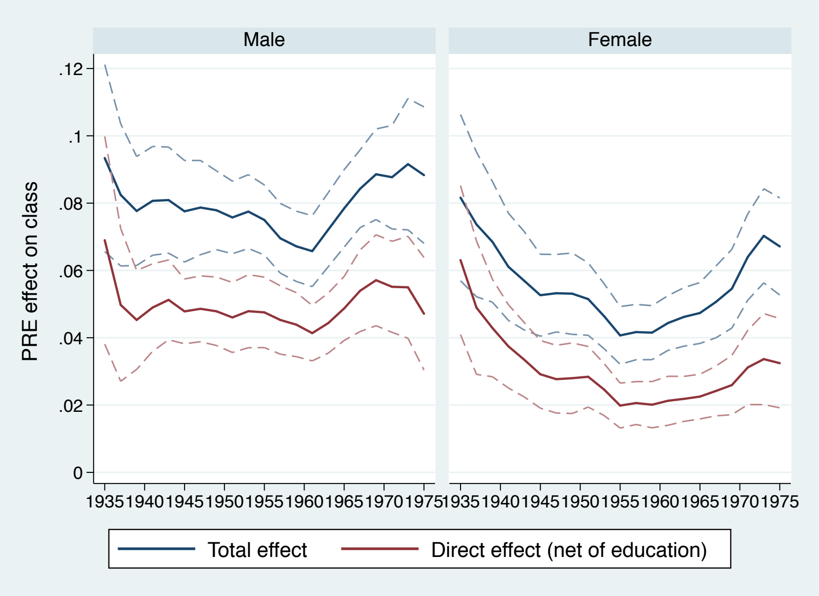

Summary

- The PRE approach seems to be viable and flexible model to analyze social mobility.
  - It produces results that are comparable to the classic LMLEM.
  - It can easily include multiple origin variables and control variables.
  - It has a clear interpretation (proportional reduction of prediction errors): How much does the knowledge of parents' characteristics improve the prediction of the child's status?

Summary

- Substantive conclusion
  - Our results indicate that social mobility increased from birth cohorts 1935 to about 1960, but then started to decrease again.
  - In general, this pattern can be observed for both men and women and both education and class. The pattern, however, is least pronounced for men's class.
  - For respondent's education the PRE approach leads to more pronounced results than LMLEM. This indicates that the structure of association changed over time for education.
  - Net of parents education, parents' class still has an effect on both respondent's education and class. As expected, the effect on class is stronger.
  - Parents characteristics have a direct effect on respondent's class, net of respondent's education.

References

- Blau, Peter M., Otis D. Duncan. 1967. The American occupational structure. New York: Wiley.
- Erikson, Robert, John H. Goldthorpe, Lucienne Portocarero (1983). Intergenerational Class Mobility and the Convergence Thesis: England, France and Sweden. The British Journal of Sociology 34(3): 303–343.
- Hout, M. 2004. How Inequality May Affect Intergenerational Mobility. S. 969–987 in: K. M. Neckerman (ed). Social Inequality. New York: Russel Sage.
- Jann, Ben, Benita Combet. 2012. Zur Entwicklung der intergenerationalen Mobilität in der Schweiz. Swiss Journal of Sociology 38(2): 177–199.
- Kerr, Clark, John. T. Dunlop, Frederick H. Harbison, Charles A. Meyers. 1960. Industrialism and industrial man. Cambridge: Harvard University Press.
- Lipset, Seymour Martin, Reinhard Bendix. 1959. Social Mobility in Industrial Society. London: Heinemann.
- Theil, Henri. 1970. On the estimation of relationships involving qualitative variables. American Journal of Sociology 76(1): 103–154.
- ie, Yu (1992). The Log-Multiplicative Layer Effect Model for Comparing Mobility Tables. American Sociological Review 57(3): 380–395.